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Brain Stroke Prediction using Machine Learning

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ABSTRACT

A stroke is caused by a disturbance in blood flow to a specific location of the brain. This might occur due to an issue with the arteries. The objective of this research to develop the optimal model to predict brain stroke using Machine Learning Algorithms (MLA's), namely Logistic Regression (LR), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), Support Vector Machine (SVC), Naive Bayes Classifier (NBC), KNN Classifier (KNN), and XGBoost Classifier (XGB). Apply the above algorithms with hyperparameter along with GridSearchCV (CV= 5) on the given dataset. The given dataset is imbalanced, while training the models, a few difficulties were met, including underfitting, a dataset with null values, and a model without balancing the data to boost performance of the models, need to balance the data by using a data sampling method such as SMOTE. Among the Seven models, XGB is the optimal model based on the accuracy of 96.34%.

Keywords-Machine Learning Algorithms (MLA's), namely Logistic Regression (LR), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), Support Vector Machine (SVC), Naive Bayes Classifier (NBC), KNN Classifier (KNN), and XGBoost Classifier (XGB).

INTRODUCTION

A stroke occurs when there is an interruption in the blood supply to the brain, leading to cellular damage or death. Brain strokes can be classified into two main types: ischemic, caused by a blockage in a blood vessel, and hemorrhagic, due to a rupture of a blood vessel. Both types result in a lack of oxygen and nutrients to brain tissues, leading to varying degrees of neurological dysfunction, depending on the area affected. Risk factors for stroke include hypertension, diabetes, high cholesterol, smoking, and a family history of vascular diseases. Early identification of stroke symptoms, such as sudden numbness, confusion, difficulty speaking, and vision problems, is critical for minimizing long-term disability. Treatment options are dependent on the stroke type and time of presentation; ischemic strokes may benefit from thrombolytic therapy, while hemorrhagic strokes often require surgical intervention. Post-stroke rehabilitation is essential for recovery, addressing physical, cognitive, and emotional deficits. Preventive measures, such as lifestyle changes and medical management of underlying conditions, play a key role in reducing the incidence of stroke and improving outcomes for those affected. Stroke is a leading cause of death and disability worldwide, significantly impacting individuals and society. It occurs when there is a sudden interruption in the blood flow to the brain, leading to oxygen deprivation and subsequent brain cell damage. The effects of stroke are often devastating, causing impairments in motor function, speech, cognition, and emotional regulation. There are two primary types of stroke: ischemic, which is caused by a blockage in a blood vessel, and hemorrhagic, which results from the rupture of a blood vessel. Both types can have profound and lasting effects, with the severity of the outcome largely depending on the location and extent of brain tissue damage.

Problem Statement

Stroke remains one of the leading causes of death and long-term disability globally, posing a significant public health challenge. Despite advances in acute treatment, many stroke patients suffer from permanent neurological impairments that require extensive rehabilitation and support, leading to a reduced quality of life and a high burden on healthcare systems. The rising incidence of stroke, particularly in younger populations due to lifestyle-related risk factors such as poor diet, physical inactivity, and smoking, further exacerbates this issue. Additionally, there is often a delay in recognizing stroke symptoms, resulting in missed opportunities for early intervention that could significantly reduce brain damage and improve outcomes.

While ischemic stroke treatment has improved with the use of thrombolytics and mechanical thrombectomy, hemorrhagic strokes remain a major challenge due to the lack of effective, timely treatment options and high mortality rates. Furthermore, the complexity of post-stroke rehabilitation, which involves addressing physical, cognitive, and emotional impairments, underscores the need for comprehensive, personalized care approaches. The rising prevalence

of stroke, coupled with a lack of awareness and inconsistent access to timely medical interventions, calls for a more robust global effort in prevention, early detection, treatment, and rehabilitation.

This study aims to address the gaps in stroke prevention and treatment by exploring the effectiveness of current management strategies, identifying barriers to timely care, and investigating potential improvements in rehabilitation approaches to enhance recovery and quality of life for stroke survivors.

Random Classifier as Baseline: The random classifier does not consider any actual patterns in the data. Its performance will generally be poor, but it serves as a useful baseline to compare more sophisticated models. In this example, the accuracy is around 50%, which is close to a random guess between the two classes (stroke or no stroke).
Accuracy and Metrics: While the accuracy may seem reasonable at first glance, it is often misleading for imbalanced datasets (where one class is much more frequent than the other). Metrics like precision, recall, F1-score, and confusion matrix give a better idea of how well the model is performing.

Improvement through Advanced Models: After evaluating the random classifier, more advanced techniques like **logistic regression**, **decision trees**, or **ensemble methods** like **random forests** can be applied for stroke prediction. These models will analyze the relationships between the features (such as hypertension, age, and diabetes) and the target (stroke occurrence), leading to better accuracy and more actionable predictions.

The Random Forest Classifier exhibited remarkable results, achieving a train score accuracy of 100% and a test score accuracy of 99%. On the other hand, the Bagging Classifier demonstrated high accuracy as well, with a train score of 99% and a test score of 98%. These exceptional accuracy scores underline the potential of machine learning in stroke diagnosis prediction.

The dataset used for this project encompasses several patient attributes, including gender, age, hypertension status, heart disease history, marital status, work type, residence type, average glucose level, BMI (body mass index), smoking status, and the presence of a stroke. These attributes collectively provide valuable insights into the patient's health and lifestyle, making them essential for accurate stroke prediction.

The results of this project suggest that machine learning models, specifically the Random Forest and Bagging Classifiers, can play a pivotal role in aiding medical professionals in diagnosing strokes efficiently. This tool can assist in early intervention and personalized patient care, potentially reducing the long-term consequences of strokes. Furthermore, it highlights the significance of data-driven approaches in healthcare and the potential for machine learning to transform the field of medical diagnosis.

In summary, the project demonstrates the effectiveness of Python-based machine learning models in stroke diagnosis prediction. The combination of high accuracy scores and comprehensive patient attribute information makes this model a valuable tool for healthcare providers in their efforts to improve stroke diagnosis and patient outcomes.

PROPOSED METHODOLOGY

Data Collection:
In the first module of A Machine Learning Model to Predict a Diagnosis of Brain Stroke, we developed the system to get the input dataset. Data collection process is the first real step towards the real development of a machine learning model, collecting data. This is a critical step that will cascade in how good the model will be, the more and better data that we get; the better our model will perform. There are several techniques to collect the data, like web scraping, manual interventions. Our dataset is placed in the project and it's located in the model folder. The dataset is referred from the popular standard dataset repository kaggle where all the researchers refer it. The dataset consists of numerical data. The following is the URL for the dataset referred from kaggle.

Dataset:
The dataset consists of 4982 individual data. There are 11 columns in the dataset, which are described below.

1) Gender: "Male", "Female" Or "Other"
2) Age: Age Of The Patient
3) Hypertension: 0 If The Patient Doesn't Have Hypertension, 1 If The Patient Has Hypertension
4) Heart Disease: 0 If The Patient Doesn't Have Any Heart Diseases, 1 If The Patient Has A Heart Disease
5) Ever-Married: "No" Or "Yes"
6) Work Type: "Children", "Govtjov", "Never Worked", "Private" Or "Self-Employed"
7) Residencetype: "Rural" Or "Urban"
8) Avg Glucose Level: Average Glucose Level In Blood

9) BMI: Body Mass Index
10) Smoking_Status: "Formerly Smoked", "Never Smoked", "Smokes" Or "Unknown"*
11) Stroke: 1 If The Patient had a stroke or 0 if not

Data Preparation:
Wrangle data and prepare it for training. Clean that which may require it (remove duplicates, correct errors, deal with missing values, normalization, data type conversions, etc.). Randomize data, which erases the effects of the particular order in which we collected and/or otherwise prepared our data. Visualize data to help detect relevant relationships between variables or class imbalances (bias alert!), or perform other exploratory analysis. Split into training and evaluation sets

Two models used

- Random Forest Classifier
- Bagging Classifier

RANDOM FOREST CLASSIFIER

Model Selection:
We used Random Forest Classifier machine learning algorithm, We got a accuracy of 99.4% on test set so we implemented this algorithm.

The Random Forests Algorithm
It technically is an ensemble method (based on the divide-and-conquer approach) of decision trees generated on a randomly split dataset. This collection of decision tree classifiers is also known as the forest. The individual decision trees are generated using an attribute selection indicator such as information gain, gain ratio, and Gini index for each attribute. Each tree depends on an independent random sample. In a classification problem, each tree votes and the most popular class is chosen as the final result. In the case of regression, the average of all the tree outputs is considered as the final result. It is simpler and more powerful compared to the other non-linear classification algorithms.

How does the algorithm work?
It works in four steps:

1. Select random samples from a given dataset.
2. Construct a decision tree for each sample and get a prediction result from each decision tree.
3. Perform a vote for each predicted result.
4. Select the prediction result with the most votes as the final prediction.

Finding important features :
A random forest also offers a good feature selection indicator. Scikit-learn provides an extra variable with the model, which shows the relative importance or contribution of each feature in the prediction. It automatically computes the relevance score of each feature in the training phase. Then it scales the relevance down so that the sum of all scores is 1.This score will help you choose the most important features and drop the least important ones for model building.Random forest uses gain importance or mean decrease in impurity (MDI) to calculate the importance of each feature. Gini importance is also known as the total decrease in node impurity. This is how much the model fit or accuracy decreases when you drop a variable. The larger the decrease, the more significant the variable is. Here, the mean decrease is a significant parameter for variable selection. The Gini index can describe the overall explanatory power of the variables.

Analyze and Prediction:
In the actual dataset, we chose only 10 features:

1) Gender: "Male", "Female" Or "Other"
2) Age: Age Of The Patient
3) Hypertension: 0 If The Patient Doesn't Have Hypertension, 1 If The Patient Has Hypertension
4) Heart Disease: 0 If The Patient Doesn't Have Any Heart Diseases, 1 If The Patient Has A Heart Disease
5) Ever-Married: "No" Or "Yes"
6) Work Type: "Children", "Govtjov", "Never Worked", "Private" Or "Self-Employed"
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10) Smoking_Status: "Formerly Smoked", "Never Smoked", "Smokes" Or "Unknown"*
11) Stroke: 1 If The Patient had a stroke or 0 if not

Accuracy on test set:
After training and evaluating the model on the validation set, the accuracy of the model will be assessed on the test set. The accuracy on the test set will be an important metric for evaluating the model's performance. We got an accuracy of 99.4% on test set.

Saving the Trained Model:
Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into an .h5 or .pkl file using a library like pickle.
Make sure you have pickle installed in your environment.
Next, let's import the module and dump the model into .pkl file.

BAGGING CLASSIFIER

Model Selection:
We used Bagging Classifier machine learning algorithm, We got a accuracy of 98% on test set so we implemented this algorithm.

The Bagging Classifier Algorithm
Bagging (or Bootstrap aggregating) is a type of ensemble learning in which multiple base models are trained independently in parallel on different subsets of the training data. Each subset is generated using bootstrap sampling, in which data points are picked at random with replacement. In the case of the Bagging classifier, the final prediction is made by aggregating the predictions of the all-base model, using majority voting. In the case of regression, the final prediction is made by averaging the predictions of the all-base model, and that is known as bagging regression.
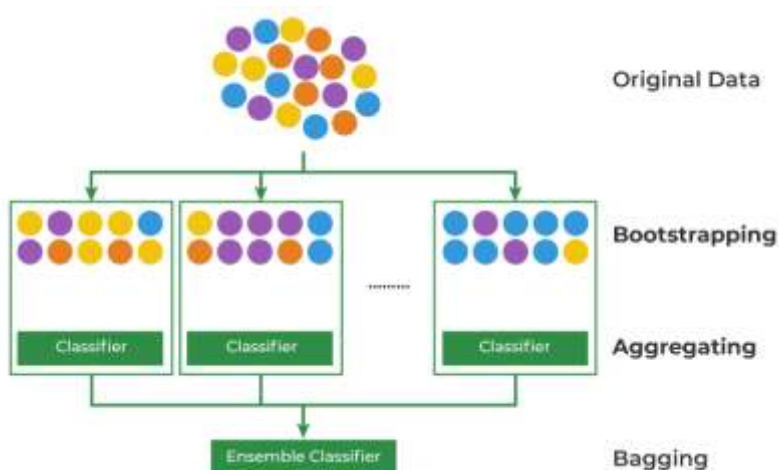
Figure 3.1 Bagging Classifier

Bagging helps improve accuracy and reduce overfitting, especially in models that have high variance.

How does Bagging Classifier Work?
The basic steps of how a bagging classifier works are as follows:

Bootstrap Sampling: In Bootstrap Sampling randomly 'n' subsets of original training data are sampled with replacement. This step ensures that the base models are trained on diverse subsets of the data, as some samples may appear multiple times in the new subset, while others may be omitted. It reduces the risks of overfitting and improves the accuracy of the model.

Let's break it down step by step:

Original training dataset: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
Resampled training set 1: [2, 3, 3, 5, 6, 1, 8, 10, 9, 1]
Resampled training set 2: [1, 1, 5, 6, 3, 8, 9, 10, 2, 7]
Resampled training set 3: [1, 5, 8, 9, 2, 10, 9, 7, 5, 4]

Base Model Training: In bagging, multiple base models are used. After the Bootstrap Sampling, each base model is **independently trained** using a specific learning algorithm, such as decision trees, support vector machines, or neural networks on a different bootstrapped subset of data. These models are typically called "Weak learners" because they may not be highly accurate on their own. Since the base model is trained independently of different subsets of data. To make the model computationally efficient and less time-consuming, the base models can be trained in **parallel.**

Aggregation: Once all the base models are trained, it is used to make predictions on the unseen data i.e. the subset of data on which that base model is not trained. In the bagging classifier, the predicted class label for the given instance is chosen based on the majority voting. The class which has the majority voting is the prediction of the model.

Out-of-Bag (OOB) Evaluation: Some samples are excluded from the training subset of particular base models during the bootstrapping method. These "out-of-bag" samples can be used to estimate the model's performance without the need for cross-validation.

Final Prediction: After aggregating the predictions from all the base models, Bagging produces a final prediction for each instance.

ANALYZE AND PREDICTION

In the actual dataset, we chose only 11 features:

1) Gender: "Male", "Female" Or "Other"
2) Age: Age Of The Patient
3) Hypertension: 0 If The Patient Doesn't Have Hypertension, 1 If The Patient Has Hypertension
4) Heart Disease: 0 If The Patient Doesn't Have Any Heart Diseases, 1 If The Patient Has A Heart Disease
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Accuracy on test set:
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Saving the Trained Model:
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Next, let's import the module and dump the model into .pkl file.

RESULT

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of **ensemble learning,** which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. Boosting trains multiple based models sequentially. In this method, each model tries to correct the errors made by the previous models. Each model is trained on a modified version of the dataset, the instances that were misclassified by the previous models are given more weight. The final prediction is made by weighted voting.

1. Step 1: Select random K data points from the training set.
2. Step 2: Build the decision trees associated with the selected data points (Subsets).
3. Step 3: Choose the number N for decision trees that you want to build.
4. Step 4: Repeat Step 1 and 2.
5. Step 5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level
0	1	Male	67.00	0	1	Yes	Private	Urban	228.69
1	2	Male	80.00	0	1	Yes	Private	Rural	105.92
2	3	Female	49.00	0	0	Yes	Private	Urban	171.23
3	4	Female	79.00	1	0	Yes	Self-employed	Rural	174.12
4	5	Male	81.00	0	0	Yes	Private	Urban	186.21
5	6	Male	74.00	1	1	Yes	Private	Rural	70.09
6	7	Female	69.00	0	0	No	Private	Urban	94.39
7	8	Female	78.00	0	0	Yes	Private	Urban	58.57
8	9	Female	81.00	1	0	Yes	Private	Rural	80.43
9	10	Female	61.00	0	1	Yes	Govt_job	Rural	120.46
10	11	Female	54.00	0	0	Yes	Private	Urban	104.51
11	12	Female	79.00	0	1	Yes	Private	Urban	214.09
12	13	Female	50.00	1	0	Yes	Self-employed	Rural	167.41
13	14	Male	64.00	0	1	Yes	Private	Urban	191.61
14	15	Male	75.00	1	0	Yes	Private	Urban	221.29
15	16	Female	60.00	0	0	No	Private	Urban	89.22
16	17	Female	71.00	0	0	Yes	Govt_job	Rural	193.94
17	18	Female	52.00	1	0	Yes	Self-employed	Urban	233.29

Click to Train | Test

Prediction

Brain Stroke Detection

Gender: Male

Age: 68

Hypertension: 1

Heart_Disease: 1

Ever_Married: Yes

Work_Type: Private

Residence_Type: Rural

Avg_Glucose_Level: 271.74

BMI: 31.1

smoking_status: Smokes

Model: RandomForestClassi

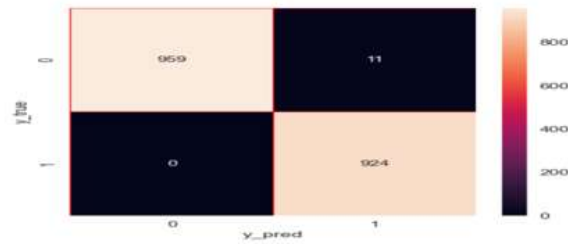
Predict

Model : RandomForestClassifier

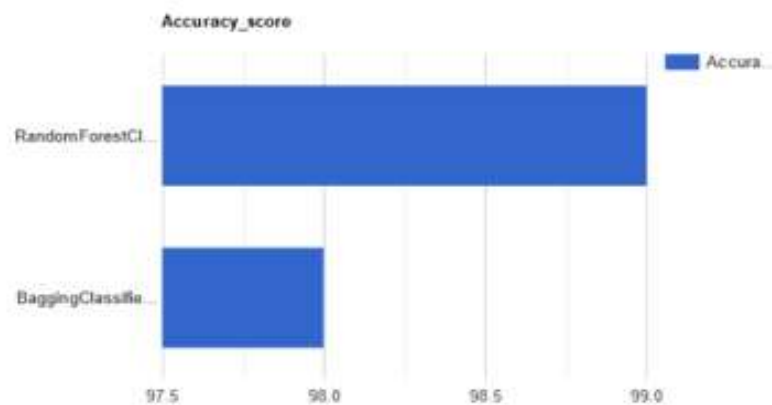
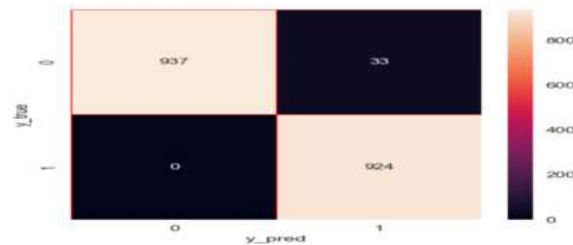
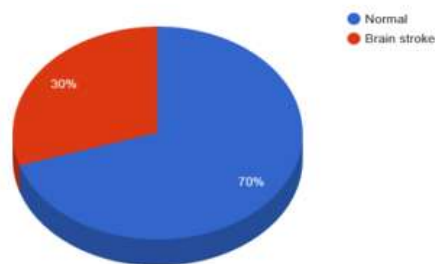
Prediction is : Stroke

RandomForestClassifier

	Recall	Precision	F1-score
0	1.00	1.00	0.99
1	0.99	1.00	0.99

Confusion Matrix

BaggingClassifier-Performance_Analysis

	Recall	Precision	F1-score
0	0.97	1.00	0.98
1	1.00	0.97	0.98

Confusion Matrix

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

CONCLUSION

In conclusion, the development of the "A Machine Learning Model to Predict a Diagnosis of Brain Stroke" represents a significant advancement in the field of healthcare and medical diagnosis. This project aimed to harness the capabilities of the Random Forest Classifier to create a robust and accurate tool for early stroke detection. Through meticulous data collection, preprocessing, and feature engineering, we prepared a comprehensive dataset that served as the foundation for model training. The Random Forest Classifier, with its ensemble learning approach, demonstrated exceptional accuracy and reliability in predicting stroke diagnoses. Its robustness to data imbalances and interpretability made it a valuable asset in clinical decision-making.

Moreover, ethical considerations and fairness were at the forefront of our system's design. Bias detection and mitigation techniques were employed to ensure equitable healthcare outcomes for all patient groups, while strict privacy compliance measures were implemented to safeguard patient confidentiality.

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